AI-Enhanced and Other Load Modelling in Modern Power Systems: A Comprehensive Review of Advances, Challenges, and Future Directions

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INFORMATION

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ABSTRACT

Load modelling is a crucial element of power system study that significantly affects the field's planning, operation, and control methods. With the increasing penetration of renewable energy sources, electric vehicles, demand-side management, and distributed generation (DG), the traditional static and dynamic load model approaches are being replaced. This paper reviews extensively the existing load modelling techniques, namely, component-based load modelling, measurement-based load modelling, and hybrid methods. In addition, advancements tuned by artificial intelligence (AI) and machine learning (ML) are critically reviewed, emphasizing improving the accuracy, flexibility, and real-time adaptability of load models. For instance, Long Short-Term Memory (LSTM) networks have demonstrated significant improvements in forecasting accuracy, while Reinforcement Learning (RL) techniques enable adaptive and real-time control of load dynamics. Special focus is laid on load modelling in conditions of imbalance, dynamic parameter identification, and integration with smart grids and active distribution networks (ADNs). The review also discusses the importance of uncertainty embedded in probabilistic and data-driven models, customer behaviour, and the stochastic nature of distributed energy resources (DERs). The areas of future study emphasized AI-assisted adaptive architectures, hybrid frameworks, and digital twin applications for resilient and intelligent load modelling.

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Abbreviations

AI	Artificial Intelligence
ANN	Artificial Neural Network
ADN	Active Distribution Network
DER	Distributed Energy Resources
DG	Distributed Generation
DSM	Demand Side Management

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DNs	Distribution Networks
IBL	Inverter-Based Load
EV	Electric Vehicle
IoT	Internet of Things
LV	Low Voltage
ML	Machine Learning
PMU	Phasor Measurement Unit
PSO	Particle Swarm Optimization
RL	Reinforcement Learning
RNN	Recurrent Neural Network
SCADA	Supervisory Control and Data Acquisition
SVM	Support Vector Machine
ZIP	Static Load Model with components: Constant Impedance (Z), Current (I), and Power (P)

Nomenclatures

Symbol	Definition	Unit
V, V_0	Bus voltage, nominal bus voltage	p.u./V
P, Q	Active and reactive power	p.u./MW/Mvar
P_0, Q_0	Nominal active and reactive power	p.u.
α_i, β_i	ZIP coefficients (constant impedance, current, power fractions)	–
R_s, X_s	Stator resistance and reactance	Ω
R_r, X_r	Rotor resistance and reactance	Ω
ω_s, ω_r	Synchronous and rotor electrical angular speed	rad/s
s	Rotor slip	–
T_e, T_L	Electromagnetic torque, load torque	Nm
J	Inertia constant	kgm^2
k_P, k_Q	Frequency sensitivity coefficients for active and reactive power	Hz^{-1}

1 Introduction

Load modelling involves representing the relationship between electrical power consumption and influencing factors such as voltage, frequency, and time, across various types of loads, including residential, commercial, agricultural, and industrial sectors [1]. It is therefore a key component since the stability analysis, planning, monitoring, control, and protection of power systems are carried out with it. Accurate load models are highly essential in the design and modification of transmission and distribution networks, as well as in the development of protective devices like circuit breakers, relays, and monitoring systems [2]. Two key aspects that define load modelling are the selection of an appropriate model structure and the computation of its applicable parameters. The two basic methods are component-based modelling and measurement-based modelling [3]. Component-based modelling relies on particular physical load data, and measurement-based modelling derives relationships from real-world data collected by sensors and meters. Although component-based models have theoretical resilience, they generally fail to capture the complexities of the real world. These two approaches differ from one another. Measurement-based approaches, particularly those that leverage smart grid technologies, nonetheless enable real-time adaptability [3]. These techniques, meanwhile, require knowledge of data processing and handling.

Static and dynamic models are two elementary forms of load models. Static models give the real and reactive power at any instant as functions of bus voltage magnitudes and frequency [4]. The dynamic load model uses active and reactive powers in contrast to voltage and time [5]. Composite load models combine the dynamic and the static for a more exact system description.

Conventional load models are challenged to describe the uncertainty associated with renewable energy sources by the growing penetration of DG, electric vehicles (EVs), and demand-side management (DSM). These uncertainties contribute to variations in system load responses that traditional models struggle to capture accurately. Different load demands are more complex due to EV charging technologies. The growing number of smart meters, phasor measuring units (PMUs), and Supervisory Control and Data Acquisition (SCADA) systems allows dynamic, real-time data-based load modelling, improving the feasibility and accuracy of models responding to grid circumstances. Furthermore, transforming load modelling through pattern recognition and adaptive parameter estimation is AI and ML [6–8]. AI technologies thus lead to stronger, more efficient networks by improving load forecasting, anomaly detection, and grid resource optimization. Hybrid systems that integrate component-based models and AI-enhanced measuring technologies provide a more complete and precise characterization of power system loads.

Probabilistic load models are gaining prominence due to their ability to incorporate stochastic variations arising from customer behaviour, distributed energy resources, and outside environmental variables, thereby including uncertainty and also using statistical distributions and real-time adaptive learning systems. These models help to lower power system analysis and planning errors. Additionally, the advancement of digital twin technologies enables the simulation and validation of load models under controlled conditions before deployment in operational power systems.

2 Classification of Load Models

Load models are represented by the relationship between power and voltage at a load bus, which is crucial for analyzing the power system. When evaluating a system's efficiency, reliability, and stability, proper load model consideration is essential. Two load models exist: static models, which capture the steady-state activity, while dynamic models address transient responses; moreover, data-driven models, which generate exact forecasts by using prior data. Given the diversity and variability of electrical loads, selecting an appropriate modeling technique is crucial to achieving realistic and reliable simulations [9]. This section provides load models according to their characteristics and emphasizes their importance in power system research and enhancing system analysis and operation, as illustrated in Fig. 1.

2.1 Static Load Model

Static load models define the relationship between active and reactive power at a load bus regarding voltage magnitudes and frequency at a given time. They are ideal for depicting static loads like resistive loads; these models illustrate the steady-state performance of loads [10]. In some cases, they are also almost similar to the behaviour of dynamic loads, like induction motors, especially when transient effects are not the primary focus. Static load models provide a simplified but advantageous method to examine power system performance by concentrating on steady-state properties. The simple mathematical framework of these models makes them a more useful instrument for power system research focused on evaluating dependability, stability, and efficiency [10].

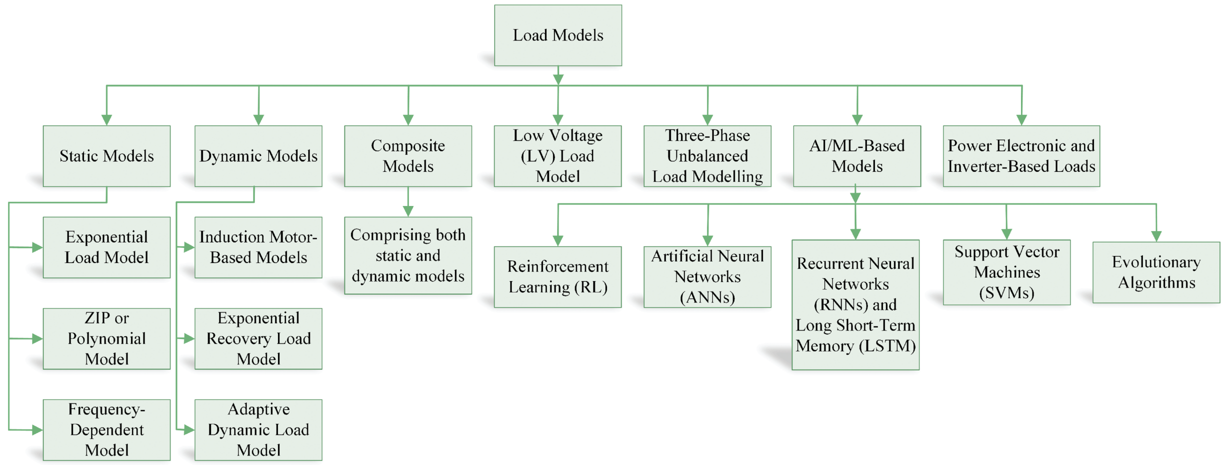

Figure 1: Load models classification

2.1.1 Exponential Load Model

An exponential model is used to establish a relationship between a load bus's power and voltage characteristics using mathematical calculations in exponential form. The function typically has a few parameters and is commonly employed to express a combination of loads [7,10]. It is possible to incorporate more components, each with a distinct exponent, into the equation [11]. The equations of the model are stated in the following manner:

$$P = P_o \left(\frac{V}{V_o}\right)^{np} \tag{1}$$

$$Q = Q_o \left(\frac{V}{V_o}\right)^{nq} \tag{2}$$

where: P_o, Q_o, and V_o are the values of active power, reactive power, and voltage at initial or nominal conditions, respectively, and V is the actual voltage, n_q and n_p are the reactive and active power exponents. It is possible to make adjustments to the n_p parameter to obtain the most accurate representation of the voltage dependency of the load.

2.1.2 ZIP or Polynomial Model

Static loads are commonly represented as constant power, constant current, or constant impedance loads, depending on the relationship between power and voltage. These three constitute the polynomial model, which goes by the ZIP model. This model can be described by Eqs. (3) and (4). Fig. 2 illustrates a typical representation of the ZIP model.

$$P = P_o \left[\alpha_1 + \alpha_2 \left(\frac{V}{V_o}\right) + \alpha_3 \left(\frac{V}{V_o}\right)^2\right] \tag{3}$$

$$Q = Q_o \left[\beta_1 + \beta_2 \left(\frac{V}{V_o}\right) + \beta_3 \left(\frac{V}{V_o}\right)^2\right] \tag{4}$$

where P_o, Q_o, and V_o are the initial values of active, reactive power, and voltage, α_1 and β_1 are the proportions of constant power, α_2 and β_2 are the proportions of continuous current, and α_3 and β_3 are the proportions of the constant impedance of active and reactive power, respectively. At initial voltage values, the sum of α_i as well as β_i will be one, indicating that the load share is constant impedance, constant current, and constant power.

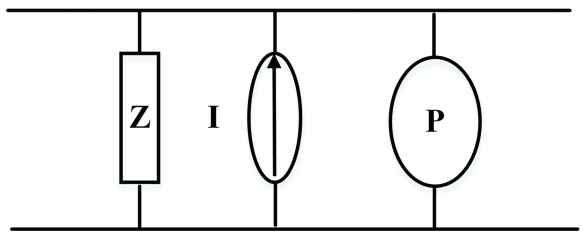

Figure 2: Polynomial or ZIP load model equivalent circuit

2.1.3 Frequency-Dependent Model

Although the frequency dependency of the load is usually not highly significant, it can still be considered while developing a load model for more precise system analysis. Incorporating a frequency-dependent element into the corresponding equations helps to establish frequency-dependent load models from either the ZIP or exponential models. In dynamic and transient studies, these models are beneficial since they enable one to explain variations in system frequency under fault. Usually reflecting load variations due to deviations from the nominal system frequency, the frequency-dependent factor alters the real and reactive power equations, enhancing model accuracy in stability assessments [12]. The equations of the model are stated in the following manner:

$$F = (1 - k(f_n - f)) \tag{5}$$

where F is the frequency factor, k represents the sensitivity factor of frequency, and f_n and f represent the nominal and bus voltage frequency.

2.2 Dynamic Load Model

Dynamic load models are time-varying representations that, considering the long-term history of voltage and frequency, including the present state, define the relationship between voltage, frequency, active power, and reactive power at any given point. These models describe loads' transient behaviour and time-varying properties; hence, they are relevant for research that includes voltage and angular stability [8,13]. Dynamic load models represent active and reactive powers as functions of voltage and time, making them essential for precisely understanding system response during disturbances or changing operational conditions. Their ability to reflect real-time load dynamics improves power system stability and reliability analysis.

2.2.1 Induction Motor-Based Models

Dynamic models that represent the active and reactive power as a function of the load bus's past and present voltage magnitude and frequency are usually formed by the equivalent circuit representation of an induction motor. This model has stator and rotor resistances, and stator, rotor, and magnetizing reactances correspondingly, which characterize the electrical behavior of the machine [13], as illustrated in Fig. 3. The rotor slip significantly influences the motor's electrical and mechanical response. Power system analysis is extensively applied to induction motor (IM) models since electric motors utilize over 70% of the total energy supplied by utilities, and a large share of them are IMs.

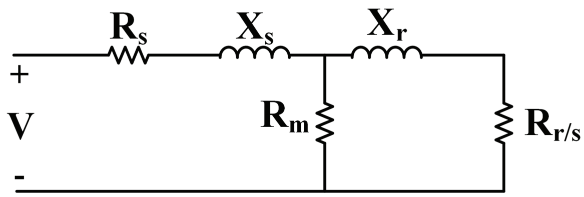

Figure 3: Equivalent circuit diagram of induction motor (IM) model

These models employing differential equations represent the electromechanical dynamics, including torque, rotor speed, and slip. Generally speaking, the mathematical representation consists of:

- Stator Voltage Equations

$$V_s = R_s I_s + jX_s I_s + E_r \tag{6}$$

where V_s is the stator voltage, R_s & X_s are the stator resistance and reactance, I_s is the stator current, and E_r is the rotor-induced voltage.

- Rotor Voltage Equations

$$E_r = \left(\frac{R_r}{s} + jX_r\right) I_r \tag{7}$$

where R_r and X_r are the rotor resistance and reactance, I_r is the rotor current, and s is the slip.

The IM can be represented in the synchronously rotating dq-reference frame for dynamic studies. The stator and rotor flux dynamics are [14]:

$$\frac{d\psi_{ds}}{dt} = v_{ds} - R_s i_{ds} + w_s \psi_{ds} \tag{8}$$

$$\frac{d\psi_{qs}}{dt} = v_{qs} - R_s i_{qs} - w_s \psi_{ds} \tag{9}$$

$$\frac{d\psi_{dr}}{dt} = -R_r i_{dr} + (w_s - w_r)\psi_{dr} \tag{10}$$

$$\frac{d\psi_{qr}}{dt} = -R_r i_{qr} - (w_s - w_r)\psi_{dr} \tag{11}$$

The electromagnetic torque and mechanical equation are given as:

$$T_e = \frac{3}{2}\frac{P}{2}(\psi_{ds} i_{qs} - \psi_{qs} i_{ds}) \tag{12}$$

$$J\frac{dw_r}{dt} = T_e - T_L \tag{13}$$

where ψ_{ds}, ψ_{qs}, ψ_{dr}, ψ_{qr}: Stator and rotor flux linkage at d-axis and q-axis

w_s, w_r: Synchronous and rotor angular speeds

T_e, T_L: Electromagnetic and mechanical load torques

P: Number of poles

J: Inertia Constant

2.2.2 Exponential Recovery Load Model

Stability studies depend on this model since it catches transient recovery behavior [5,13]. It is expressed by nonlinear first-order differential equations:

- Active Power Dynamics

$$T_p \frac{dx_p}{dt} = -x_p + P_0 \left(\frac{V}{V_0}\right)^{N_{ps}} - P_0 \left(\frac{V}{V_0}\right)^{N_{pt}} \tag{14}$$

$$P_d = x_p + P_0 \left(\frac{V}{V_0}\right)^{N_{pt}} \tag{15}$$

- Reactive Power Dynamics

$$T_q \frac{dx_q}{dt} = -x_q + Q_0 \left(\frac{V}{V_0}\right)^{N_{qs}} - Q_0 \left(\frac{V}{V_0}\right)^{N_{qt}} \tag{16}$$

$$Q_d = x_q + Q_0 \left(\frac{V}{V_0}\right)^{N_{qt}} \tag{17}$$

where:

x_p and x_q are state variables for power dynamics

T_p and T_q are time constants

N_{ps}, N_{qs}, N_{pt}, and N_{qt} define load response

P_0 and Q_0 are nominal active and reactive power values

2.2.3 Adaptive Dynamic Load Model

An adaptive dynamic load model is an extension of the ERL by introducing adaptive parameters that adjust in response to varying system conditions. While the ERL captures transient recovery behavior through fixed nonlinear differential equations, the adaptive model incorporates state-dependent dynamics, making it more suitable for systems with variable operating conditions [15,16]. Though the power is a function of the voltage multiplied by the state variable, the model exponential has the features of the recovery model [17].

- Active Power Dynamics

$$T_p \frac{dx_p}{dt} = -x_p \left(\frac{V}{V_0}\right)^{N_{ps}} + P_0 \left(\frac{V}{V_0}\right)^{N_{pt}} \tag{18}$$

$$P_d = x_p \left(\frac{V}{V_0}\right)^{N_{pt}} \tag{19}$$

- Reactive Power Dynamics

$$T_q \frac{dx_q}{dt} = -x_q \left(\frac{V}{V_0}\right)^{N_{qs}} + Q_o \left(\frac{V}{V_0}\right)^{N_{qt}} \tag{20}$$

$$Q_d = x_q \left(\frac{V}{V_0}\right)^{N_{qt}} \tag{21}$$

2.3 Composite Load Model

Comprising both static and dynamic models, the composite load model offers a more realistic representation of total loads in distribution systems. It includes:

- A static component is typically modeled using a ZIP, exponential, or frequency model, which is represented by Eqs. (1)–(5).
- A dynamic component, generally based on the induction motor model to capture the transient behaviour of motor-driven loads, which is represented by Eqs. (6)–(17).

This composite model assembles these parts, defining fractions of total active and reactive power for each component. For example, a certain percentage of the load might be modeled using a static ZIP portion, and the remainder is modeled using induction motors. By including the load of both types, the model can capture the fast voltage-sensitive response associated with electronic/static loads and the slower dynamic response associated with the rotating machines. Composite models are particularly useful in voltage and frequency stability studies, as they offer a more realistic response than purely static or dynamic models [13,18]. Composite voltage and frequency stability assessment models are typically regarded as advantageous because they provide a better response than purely static or dynamic models. A standard industry example is the WECC CMPLDW model, which specifies a composite load structure by defining a unified load structure that combines ZIP, induction motors, and optional electronic load components for dynamic simulations in large-scale power systems [19].

2.4 Low Voltage (LV) Load Model

Usually, LV networks are represented using lumped models. However, demand-side management and the inclusion of renewable DGs highlight the need for more complete LV load modelling. The most recent research focused on characterizing the consumption patterns of LV household loads. Few research has been conducted on developing physical models that accurately represent electrical characteristics. Two models typically used to depict LV loads are the exponential and ZIP models. Using data from smart meters and machine learning techniques, it can generate aggregated ZIP load models for LV networks [20–22].

2.5 Three-Phase Unbalanced Load Modelling

Low-voltage distribution systems are inherently unbalanced due to the prevalence of single-phase residential and commercial loads, and are further unbalanced due to the uneven distribution of rooftop PV and stochastic EV charging. Conventional balanced single-phase equivalents often fail to capture all the phenomena that may arise in the systems, such as negative-sequence currents, unequal phase voltage drops, and losses that may increase under asymmetrical loading. Phase-domain models represent each phase with its specific impedance and mutual coupling elements, offering high accuracy but requiring detailed feeder and load information. On the other hand, symmetrical component models change voltages and currents into components that are positive, negative, and zero sequences.

This approach allows for the quantification of imbalance in the case of voltage stability and fault studies with great efficiency, but there are still some limitations with non-linear loads [17,23].

Unbalance in feeders that are primarily influenced by power-electronic and nonlinear devices is typically done by harmonic load flow or electromagnetic transient (EMT) simulations. These simulations can capture distortion-driven asymmetry and frequency coupling effects. Several case studies on urban LV feeders have found that high PV and EV penetration may lead to an increase in the voltage unbalance factor (VUF) beyond set limits that are considered acceptable, thus local power quality and stability concerns may arise. Hence, the accurate three-phase unbalanced modeling is essential for modern active distribution networks, enabling reliable assessment of system losses and compliance with IEEE Std. 1159/IEC 61000 limits, and the robust planning of the mitigation strategies [24,25].

2.6 Power Electronic and Inverter-Based Loads

With the growing penetration of electronic devices, variable-speed drives, and distributed energy resources, inverter-based loads (IBLs) have become a critical component of modern power systems. IBLs interface with the grid through a fast-switching converter, which results in low inertial, fast response time, currents or power injections governed by the control system, and overall flexibility to achieve operating functions such as power factor correction and providing voltage/frequency support. However, these factors can lead to harmonic emissions, weak grid interactions, and frequency/impedance-dependent behavior [26]. IBLs can be modelled depending on the study focus, typically average-value models that account for control dynamics without switching harmonics. In contrast, in detail, electromagnetic transient (EMT) models are essential when investigating converter-driven oscillations, resonances, and harmonic propagation.

The increasing share of inverter-based loads (IBLs) impacts system stability and load model interactions. The lower inertia of IBLs can worsen frequency excursions, and embedded control loops can change voltage recovery and damping characteristics relative to conventional induction-motor-dominant loads. Moreover, large-scale IBLs will have harmonics that can interact with feeder impedance to produce resonance and power quality problems. Recent work has demonstrated that hybrid load models using ZIP, harmonic, and inverter-based loads are more effective than purely ZIP loads at representing a mixed load population during electrical disturbances [27]. Therefore, accurate modelling of IBLs is essential to reporting voltage stability, harmonic behaviour, and converter–network interactions in future active distribution networks.

Beyond from these classifications, the role of standards, including those developed by IEEE and IEC, are important to the development of load modeling practices. The IEEE Task Force on Load Representation has defined widely used static and dynamic models such as ZIP, exponential, and induction motors that can be used as basic models for stability and planning studies [12]. The WECC Composite Load Model (CMPLDW) [19] demonstrates that such recommendations evolve into practical tools for large-scale simulations. IEC standards, particularly the IEC 61000 series, provide complementary guidance on aspects such as power quality, harmonics, and validation protocols, ensuring that models are not only mathematically accurate but also operationally reliable and efficient. So, these standards influence both model selection and validation, bridging the gap between academic research and industrial application, and laying the foundation for advanced AI-driven modeling approaches discussed in the following section.

3 Artificial Intelligence in Load Modeling: Techniques, Applications, and Advancements

The landscape of load modeling in power systems is rapidly evolving toward data-driven methodologies with the advancement of artificial intelligence (AI). Although conventional modeling approaches remain mathematically sound, they often fail to capture nonlinearities, fast-changing load behaviors, and the effects of new technologies (like electric vehicles (EVs) and distributed energy resources (DERs)). The future of technology-enhanced approaches using AI, including new algorithms, models, and tools, can solve these challenges by learning complex patterns from data and adapting in near real-time to grid dynamics [28]. Recent reviews have examined the broader role of AI in microgrids, particularly in design, control, and maintenance [29].

3.1 Common AI Techniques Used in Load Modeling

The modern power systems, being complex, are a result of the integration of renewable energy, prosumer participation, and uncoordinated electric vehicle charging, which has introduced a need for modeling techniques that can learn from data and respond to real-time system dynamics. AI-based techniques have become instrumental players in this sector, and they can handle nonlinear relations, uncertain conditions, and time-varying load features [28]. The focus here is on the most popular AI algorithms for load modeling, their features, examples of use, and drawbacks.

3.1.1 Artificial Neural Networks (ANNs)

Artificial Neural Networks are the most extensively applied AI techniques in load modeling, due to their strong capability to approximate nonlinear and complex relationships. An ANN is essentially interconnected layers of neurons (input, hidden, and output) through which the voltage, frequency, and other features are mapped to active and reactive power outputs.

For load modeling, the ANNs have been employed for both:

- Static load estimation, where the network maps voltage and frequency inputs to active and reactive power outputs.
- Dynamic modeling, where the architectures of the ANN obtain learning of the temporal behavior of the patterns using the snapshot data from the SCADA system or the PMUs.

ANNs are trained by supervised learning algorithms such as backpropagation, where the past input-output pairs (like voltage profiles and power consumption data) are used to train the network weights. According to the studies, ANN-based load models produce an average of 20%–30% decrease in mean absolute percentage error (MAPE) compared to polynomial ZIP models [30]. This makes it highly suitable for real-time applications such as "demand forecasting, anomaly detection, and load decomposition." On the other hand, ANNs need good-quality training datasets, and their "black-box" nature makes them less understandable for system operators. Overfitting and poor generalization to unseen scenarios are typical problems if regularization and cross-validation are not properly employed [31].

3.1.2 Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM)

While ANNs perform well for static load mapping, they cannot represent time dependencies. RNNs address this limitation by introducing recurrent loops in the network, allowing information from previous time steps to influence current predictions. This architecture makes RNNs suitable for representing the sequential behavior of electrical loads, especially in a dynamic system where the load characteristics change over time [32].

LSTM, a more advanced type of RNN, provides memory cells and gating mechanisms (input, output, and forget gates) that enable the model to learn long-term dependencies without the vanishing gradients problem. Such architectures perfectly fit the following uses:

- Short and medium-term load forecasting improves prediction accuracy under fluctuating demand conditions [33].
- Time series reconstruction of customers' behavior, which captures cyclical and seasonal effects [34].
- Modeling load changes in the EV charging patterns, where the load dynamics demonstrate the sequential patterns [35].

Recent research indicates that LSTM-based models outperform traditional forecasting models such as ARIMA and shallow ANNs by 15%–25% in forecasting error (e.g., MAPE) in highly variable environments [36]. Despite their strong performance, they require substantial computational resources, are complex to train, and are quite sensitive to data quality. In addition, hybrid approaches integrating digital twins with type-2 fuzzy logic controllers and neural networks have shown promise for advanced system management.

3.1.3 Support Vector Machines (SVMs)

Support Vector Machines (SVMs) are supervised learning algorithms widely applied for classification and regression problems. SVMs in load modeling can be employed to [37]:

- Classification of load types (resistive, motor, mixed) according to voltage/current signatures.
- Load forecasting under a noisy and uncertain condition using Support Vector Regression (SVR).

SVMs operate by identifying the optimal hyperplane, which either maximizes the margin between data classes (in classification) or minimizes the prediction error (in regression), and typically employs kernel functions for non-linear transformations. Compared to ANNs, SVMs are less prone to overfitting and are more resilient, especially in spaces with high dimensions, and work well with smaller training datasets [38]. On the other hand, SVMs are restricted in their power to represent long-term temporal dependencies. Thus, they are not well-suited for dynamic modeling unless they are combined with some characteristics or features that are time-lagged or combined with other methods, e.g., Kalman filters and wavelet transforms.

3.1.4 Evolutionary Algorithms: Genetic Algorithms (GA) and Particle Swarm Optimization (PSO)

Genetic Algorithms and Particle Swarm Optimization are heuristic optimization methods inspired by biological evolution and swarm intelligence. These algorithms differ from gradient-based learning methods as they do not require differentiable objective functions and can escape local minima, making them suitable for complex, nonlinear optimization problems [39,40].

In load modeling, GA and PSO are mainly applied to:

- Estimating parameters of composite load models (e.g., adjusting ZIP + IM parameters).
- Optimizing model structure (e.g., selecting features or configuring ANN architecture).
- Minimizing a cost function in an error-based training process for black-box models.

For instance, GA follows the principle of natural selection by choosing, crossing over, and mutating candidate solutions. PSO portrays the collective behavior of the particles moving through the solution space; they change their position and speed according to the best solution for the personal and global spheres.

These two methods have effectively identified nonlinear, multidimensional parameter sets in measurement-based modeling [40]. The major drawback of these methods is that they are computationally expensive, which could be a problem regarding real-time applications. They are typically employed in offline calibration or hybrid setups with other AI algorithms to balance speed and accuracy.

3.1.5 Reinforcement Learning (RL)

Reinforcement Learning (RL) represents a significant advancement in the load modeling field that brings a fundamental change from passive to active learning mechanisms. In RL, an agent interacts with an environment (e.g., a power grid or a simulated load system) by taking actions, receiving feedback (rewards or penalties), and iteratively learning to maximize cumulative reward over time through trial and error [41]. Applications of RL in load modeling and control include:

- Adaptive load shaping for demand response.
- Online learning of consumer patterns under uncertainty.
- Real-time optimization of load estimators in smart grid environments [41].

RL is particularly suited for non-stationary and partially observable environments, where training data is scarce or system dynamics evolve, rendering supervised learning approaches less effective [41]. On the other hand, problems such as stability during convergence, safety assurances, and the need for simulation environments for training still limit the widespread usage of this approach [42]. Recent research explores the combination of RL with digital twin environments to simulate grid response safely during training, and deep RL (e.g., DDPG, PPO) for high-dimensional state-action modeling [43]. Recent works also highlight that AI-driven strategies for reactive power management in hybrid AC/DC microgrids demonstrate quite significant improvements in converter utilization and stability [44].

Artificial intelligence (AI) is a significant tool in power system load modeling, as it is a data-driven approach to solving problems traditionally addressed using analytical methods. The AI techniques have been implemented for various purposes, such as short and long-duration load prediction, real-time load estimation, and adaptive model calibration. The models, like Artificial Neural Networks (ANNs) and Long Short-Term Memory (LSTM) networks, have proven to be highly effective in capturing nonlinear temporal dependencies by using past data, weather conditions, and market signals to predict load behavior. On the other hand, the optimization algorithms such as Particle Swarm Optimization (PSO) and Genetic Algorithms (GA) are extensively used to accomplish the parameter identification in composite load models, such as estimating ZIP and induction motor parameters with improved precision. Also, the AI methods have been very effective in detecting anomalies like sudden load changes and events of abnormal consumption and classification of different load types that rely on the features of the voltage and current. In the smart grids' context, AI is also instrumental in facilitating the implementation of DSM and demand response strategies by providing predictive consumption trends and supporting the automated control schemes in distributed energy environments [8]. A comparative summary of these commonly applied AI techniques, including their strengths and limitations, is provided in Table 1. The integration of smart transformers has also been shown to enhance the optimal management of microgrids.

Table 1: Comparative summary of common AI techniques used in power system load modeling

AI technique	Application	Data needs	Interpretability	Strength	Limitation	Deployment maturity	Example application (Case Study)
ANN	Static and dynamic load estimation	High (large training data)	Low	Handles nonlinear relationships	Requires a large training dataset	Mature	Short-term load forecasting & DSM
RNN/LSTM	Time-series forecasting, EV patterns	High (long sequences)	Low-Medium	Captures temporal dependencies	Computationally intensive	Emerging	EV charging demand prediction
SVM	Load type classification, regression	Moderate	Medium	Effective on small/noisy datasets	Poor at modeling sequential behavior	Medium	Voltage/ reactive power control in smart grids
PSO/GA	Parameter estimation, structure tuning	Moderate	Medium	Explores complex parameter spaces	High computational cost	Medium	Power quality disturbance classification
Reinforcement Learning (RL)	Adaptive DSM, online estimation	Requires simulation/ digital twin	Low	Learns from interaction with the environment	Needs a simulation environment & stable convergence	Low	Optimal DG placement & load parameter tuning

3.2 Challenges and Limitations of AI-Based Load Modeling

The adoption of AI in load modeling has clear advantages, including the ability to capture highly nonlinear and time-varying characteristics, robustness against noise or incomplete data, and the possibility of transferring learned knowledge across different customer types. Data sources such as smart meters and PMUs provide valuable inputs for these models. However, several challenges remain. AI models are often data-hungry, require high computational resources for training, and may act as "black boxes," offering limited interpretability and transparency to system operators. Recent techniques, such as transfer learning, will reduce data requirements by reusing knowledge from related tasks, while lightweight architectures are being explored to lower computational costs. Moreover, their generalizability is restricted, as models trained under specific grid conditions, seasons, or geographic regions may not perform well in different contexts. To overcome these limitations, recent studies suggest hybrid AI frameworks that combine neural networks with traditional load modeling, explainable AI (XAI) approaches to improve trust, federated learning for privacy-preserving training across decentralized datasets, and AI-powered digital twins for simulation and validation [45]. Together, these developments point toward the creation of accurate, adaptive, and resilient AI-driven load models for future power systems, as highlighted in the promising works of Maraaba et al. [8] and Zheng et al. [9].

4 Distribution System

The distribution system is an essential interface between the high-voltage transmission network and end users to ensure an effective power supply. At first, distribution networks (DNs) were mostly used as conduits for unidirectional power and energy movement. However, technology has evolved DNs into active distribution networks (ADNs), using distributed generation (DG) to improve reliability, availability, and power quality [46,47].

Modern ADNs are developing toward smart distribution systems since they include advanced communication infrastructure and enable bidirectional power delivery, network elements like transmission line effects, active shunt capacitors, and grid-connected DGs. The present ADN comprises various static, dynamic, and composite loads. These components, taken together, help determine the total load at particular distribution buses, affecting the power system's stability and operational equilibrium. Studies of voltage and angular stability, as well as evaluation of the equilibrium operating conditions of the system, depend on load modeling in distribution networks. Robust load modelling methods must evolve to reflect the growing complexity of load behavior as distribution systems move from passive to active and finally to smart networks. Future studies should improve load models to fit real-time adaptability, increase DG integration, and apply machine learning methods for enhanced forecasting accuracy [2,46,47]. Essential elements of power system analysis are load models, which reflect the behaviour of electrical loads under different operating conditions. Evaluating system stability, reliability, and efficiency depends much on accurate load modelling. Load models are categorized according to their capacity to depict several structures of load behaviour, including data-driven, dynamic, and stationary elements. Several load models are arranged in this part, and their significance is for research on power systems.

In traditional passive distribution networks, load modeling is based on aggregated static or composite models, because loads were unidirectional with predictable consumption. These models assume stable consumption habits and utilize steady-state analysis. In ADNs, the presence of distributed generation (DG), electric vehicles (EVs), and demand-side management increases bidirectional power flows, increases uncertainty, and results in rapid load changes. Load modeling in ADNs therefore requires advanced approaches, especially measurement-based and hybrid methods, which can be adapted to real-time, capture unbalanced conditions, and incorporate stochastic sources of variation. The differences in the ways that load modeling from ADNs is unique highlight how adaptive and data-driven load models are important for proper stability assessment and reliability assessments.

5 Load Model Identification Technique

Power system analysis depends on proper load model identification since it guarantees that the models accurately represent actual system behaviour. Component-based and measurement-based techniques are two groups into which load model identification techniques fall.

- **Load Model Structure Selection:** The characteristics of the load bus determine the appropriate load model structure to be chosen. While planners and academics apply IEEE standard test methods to establish concepts for planning and operational assessments, power system operators concentrate on buses within their control areas. Different modelling structures can be used to effectively depict load behaviour depending on the type of problem [48].
- **Parameter Identification:** Estimating the model parameters to fit the load response behaviour best is the essence of parameter identification. It could classify it as a data-fitting issue, in which observed data is used to define mathematical models. Load model parameter identification can be accomplished using two primary approaches [49].

5.1 Measurement-Based Approach

Real-time data from field devices, including smart meters, Phasor Measurement Units (PMUs), and SCADA systems, form the foundation of measurement-based load modeling. These readings give high-resolution voltage, current, and power flow data, thus enabling precise load characterization. Large datasets are processed using this method, employing statistical regression, artificial intelligence, and pattern recognition methods to derive significant insights [4,18]. The main approaches for load parameter identification are generally classified as measurement-based or component-based, as illustrated in Fig. 4.

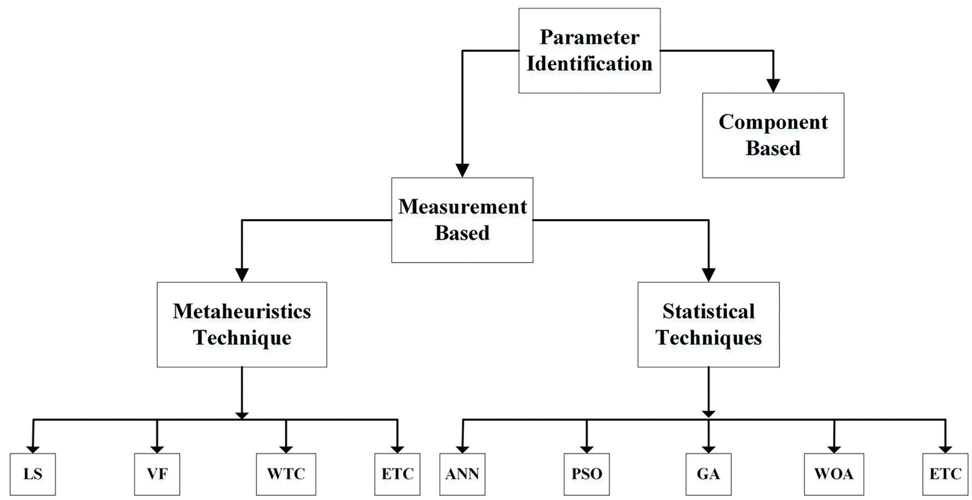

Figure 4: Approaches for load parameter identification

Measurement-based modelling using real-time data allows models to be updated and perform dynamic system analysis. This real-time adaptability is particularly beneficial when load behavior varies rapidly, like in industrial areas, metropolitan cities, and renewable energy-driven grids. Furthermore, these models are useful for demand-side management, system control, and disturbance analysis. Measurement-based approaches offer a significant advantage by capturing actual load behavior without relying on detailed prior knowledge of individual load components. However, they also introduce challenges such as the need for high-performance computing resources, substantial data storage, and potential inaccuracies caused by incomplete or noisy data. Advanced filtering and preprocessing methods, including Kalman filters and deep learning algorithms, help to increase accuracy and resilience [7]. There have been recent applications of artificial neural networks (ANNs) [8], recurrent models (i.e., LSTMs) [9], and the use of metaheuristic optimization methods such as PSO and GA [37,38] to enhance parameter identification from real-time measurement datasets. The structured steps involved in estimating load parameters are further summarized in the block diagram shown in Fig. 5. Hybrid approaches that combine physics-based models with AI-based learning frameworks have shown significant improvements in both accuracy and adaptability.

Typically based on the load bus of interest, the measurement-based approach to load modelling follows a structured process: (a) identification of the model structure; (b) data acquisition using measurement devices such PMUs and smart meters; (c) formulation of a load model that represents the observed characteristics; (d) application of an optimization technique to minimize the cost function and determine load parameters; (e) evaluation of the cost function through testing; and (f) model validation to ensure accuracy. The load model achieves reliability from this iterative refinement process [3,7]. The error function used in parameter identification is expressed as:

$$f(e) = \frac{1}{N} \sum (P_m - P_e)^2 + (Q_m - Q_e)^2 \tag{22}$$

where P_m and Q_m are the measured active and reactive powers at sample k, while P_e and Q_e are the corresponding estimated powers obtained from the load model. N represents the total number of samples considered. By minimizing this error function through optimization techniques such as Particle Swarm Optimization (PSO), Improved PSO, or Genetic Algorithms (GA), the estimated load responses can be matched closely with actual measurements. This allows the model to effectively capture the dynamic and time-varying nature of electrical loads, making measurement-based techniques widely applicable in power system research.

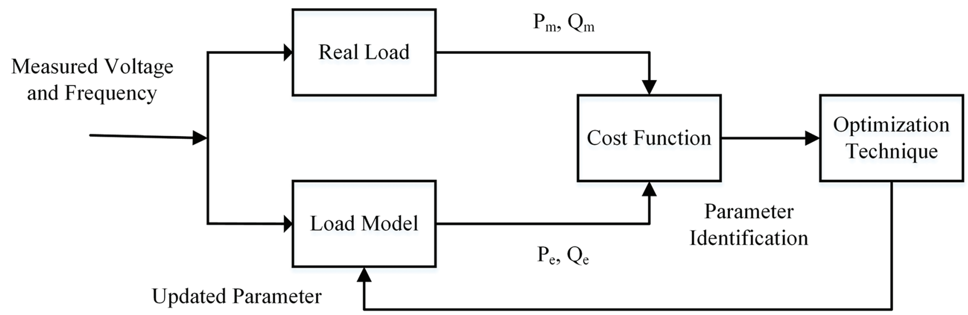

Figure 5: Block diagram for estimation of load parameter

5.2 Components-Based Approach

The component-based method is a technique that creates an overall load model by combining models of specific electrical components under consideration. A comprehensive understanding of load composition is necessary to implement this strategy. This includes the percentage of power consumption that is contributed by each type of load, such as residential, industrial, or commercial loads. The advantage of this method is that it offers a physically relevant representation of the load; however, it requires collecting a substantial amount of data and simultaneously classifying different types of loads [3].

5.3 Hybrid-Based Approach

In hybrid load modeling, component-based and measurement-based methods are combined through a mechanism that is implemented in a complementary manner. Component-based models are prioritized when reliable physical parameters (such as motor ratings, static ZIP coefficients, and load composition data) are available, offering a physics-informed baseline. On the other hand, measurement-based models gain more significance if there is a lot of field data, such as PMU or AMI measurements, that provide real-time adaptation and parameter calibration. Actually, hybrid models are often run in an iterative manner: a component model defines the structural framework, and measurement data are used to continuously update the parameters so that the model remains accurate under different operating conditions. This combination makes hybrid approaches retain the features of physics-based models in terms of interpretability and those of data-driven methods in terms of adaptability [50]. Using real-time measurements and past data, hybrid models provide better flexibility to fit shifting load patterns. Often combined with hybrid approaches to maximize parameter estimates and improve predictive capabilities, machine learning technologies such as artificial neural networks and reinforcement learning find applications [51].

Representative studies for different categories of load models, including static, dynamic, composite, AI-based, and LV models, are summarized in Table 2.

Table 2: Load model and types

Type	Author	Model
Static	Vignesh et al. [52]	ZIP
	Kundur [53]	ZIP & Exponential
	Lee et al. [54]	ZIP
	Renmu et al. [18]	ZIP
Dynamic	Naderi et al. [27]	IM
	Hill [5]	Exponential recovery
	Karlsson et al. [55]	Exponential recovery
Composite	Han et al. [56]	ZIP + IM
	Choi et al. [57]	ZIP + IM
	Bai et al. [58]	Exponential + IM & ZIP + IM
AI Based	Ku et al. [59]	ANN
	Keyhani et al. [60]	ANN
LV	Zhang et al. [61]	Analytical
	Collin et al. [22]	Equivalent circuit

6 Advancements and Future Research Directions

Load modelling has gained increased attention with new load types, the transformation of distribution networks from passive to active systems, and the evolution of smart grids. This section highlights advancements and potential research directions in load modelling.

6.1 Research Trends

Load modelling and identification are areas of study that have been around for a long time, but are still changing. System equilibrium conditions were initially determined using static models. Later on, dynamic and composite models were introduced [60] to improve stability analysis. New modelling approaches are needed to accurately depict modern power system behaviour with increasing penetration of renewable energy and integrated distribution generation (DG) [47]. Research efforts to balance accuracy and computational practicality still impact developments in this field.

Since measurement-based methods reflect real-time system activity, they have outperformed component-based methods. Several recent studies have adopted statistical and machine learning-based identification methods to improve model accuracy and flexibility. An innovative substitute that allows adaptable real-time model changes without constant re-training is artificial intelligence (AI)-driven load modelling [6,9,59].

6.2 Areas of Future Research

Several important areas need more research, given the limits of present modeling methods:

- **Unbalanced Load Modelling:** Most current models assume that the system is balanced; however, low voltage (LV) feeders are usually so asymmetrical that the difference can be rather significant. The future work should be focused on designing three-phase exponential recovery load

(ERL) models for unbalanced feeders, and using such indices as Voltage Unbalance Factor (VUF) for IEEE 33-bus and 69-bus test systems for experimental validation. Methods like adaptive filtering, sequence decomposition, and wavelet-based analysis can be supplemented with AI/ML tools (e.g., deep neural networks, reinforcement learning) to provide an automatic feature extraction and a quick parameter adaptation process.

- **Real-Time Adaptive Modelling:** Load performance is affected by seasonal, geographical, and time factors. Therefore, future research can explore creating an adaptive load model considering continuous data from PMUs and smart meters. Real-time execution can be checked through criteria such as mean absolute percentage error (MAPE), root mean square error (RMSE), and computational latency.
- **AI/ML-Driven Hybrid Modelling:** Implementing AI/ML in hybrid frameworks that combine measurement-and component-based approaches can lead to further advancement in the field. The research question focuses on the extent to which ANNs, LSTMs, and RL can be utilized to lower noise-induced errors in estimation and enhance the system's adaptability. The percentage of accuracy improvement over that of conventional models and the ability to operate under uncertainty are the criteria for reporting results.
- **Reinforcement Learning and SVMs:** RL and SVM-based load identification techniques can be further developed for online estimation and demand-side management. In the future, their performance can be compared with that of metaheuristics (e.g., GA, PSO) on standardized event data sets, and the benchmarks, such as convergence speed, scalability, and accuracy, can be reported.
- **Integration of DG and Inverter-Based Loads:** As distributed generation (DG) and inverter-based resources have become more prominent, composite load models must be changed to include converter dynamics. Future research should simulate hybrid ZIP + IM + IBR load models for different DER penetration scenarios and verify with small-signal stability margins, harmonic distortion indices (THD), and frequency response metrics.
- **Big Data and Smart Meter Analytics:** Load modelling can be improved with the large volumes of data produced by IoT devices, PMUs, and smart meters. The development of enhanced data mining, clustering, and real-time processing methods will help to use this data effectively.
- **Emerging Technologies:** Recent advances such as quantum computing, federated learning, and digital twins open new possibilities for future load modeling. Quantum computing can accelerate optimization and forecasting tasks for highly complex systems. Federated learning enables privacy-preserving collaboration across decentralized datasets without requiring direct data sharing, and it is especially important for utilities and prosumers. Digital twin frameworks provide real-time platforms to simulate, calibrate, and validate load models in virtual environments before deployment in the real world. Together, these technologies can enhance and improve adaptability, security, and accuracy in next-generation load modeling.
- Another important area of future research concerns the role of load modeling in enhancing **power system resilience and reliability**. Extreme weather events, such as heat waves, storms, and floods, which can cause rapid and unpredictable changes in load demand and also cyber-physical threats, may disrupt data integrity or system operations. So, accurate and adaptive load models will support resilience by enabling operators to anticipate abnormal conditions as well as implementing preventive control actions, and design recovery strategies. In particular, real-time measurement-based and AI-driven models can improve situational awareness and response

capability, thereby strengthening both short-term reliability and long-term resilience of power systems.

7 Conclusion

Load modelling approaches and parameter identification strategies are thoroughly reviewed in this article, which classifies load models into static, dynamic, composite, and artificial intelligence-based systems. Every modelling technique has different strengths and limitations; measurement-based approaches and hybrid modelling techniques are becoming increasingly important in response to the growing complexity of contemporary power systems.

Despite advancements, load modelling still presents various challenges, especially in integrating distributed energy resources (DERs), power electronics, and demand-side control. Addressing these problems requires improved real-time flexibility, unbalanced disturbance analysis, and computational efficiency. Enhancing model accuracy and scalability is expected to rely heavily on artificial intelligence and data-driven methods. Key takeaways from this review include the effectiveness of AI/ML methods such as ANNs, LSTMs, and RL in capturing nonlinear and time-varying behaviors, and the potential of hybrid models to combine physical interpretability with data-driven adaptability. The most promising future directions also involves developing real-time adaptive models using smart meter and PMU data, adopting explainable AI (XAI) to improve transparency and operator trust as well as applying federated learning and digital twins for secure and realistic model validation, and incorporating resilience-focused modeling to address extreme weather events and cyber-physical threats.

Accurate and dynamic load models become critical as power systems transition toward smarter, more flexible networks. Future studies should develop hybrid methods that combine artificial intelligence-driven technologies with real-time data analytics to ensure improved system reliability, stability, and efficiency. Robust and adaptive power networks capable of adapting to the dynamic nature of modern energy consumption will shape the ongoing progress of load modelling.

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